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RICIAN PERTURBED NOISE REMOVAL OF MR IMAGES USING NON LOCAL MEANS FILTER

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Abstract: A novel edge preserving nonlocal means (NLM) technique pertaining to MR images perturbed with Rician noise is presented in this paper. Earlier proposed techniques over-smoothes the MR image and hence edge preservation was difficult.Also nonlocal means filter when carried-out on 3D images, slows down the denoising process. In our work we have optimized the denoising algorithm to achieve higher speed and better accuracy using principal component analysis technique. We have tested our proposed method on simulated, clinical and pathological image sets. With a wide variety of evaluation metrics such as PSNR, BC, UQI and visual inspection itis found that the proposed technique outperforms other techniques qualitatively and quantitatively. The proposed method is 6.8 times faster than all other methods in comparison.

***Index Terms* - Component,formatting,style,styling,insert.**

I. Introduction

MR images plays very important role in medical field as these images are analyzed and studied thoroughly for diagnostic purposes and hence MR images should be of high quality. However, various noises can corrupt the MR image sequences while image acquisition process. A number of papers on MR image denoising can be found in literature. Some noise can be easily dealt with and some are not. Rician noise is one among them asit is signal dependent hence difficult to remove. In this paper we have considered MR image sequences corrupted with Rician noise. Denoising can be dealt in spatial as well as in transform domain.In transform domain, image/video is subjected to any suitable transform e.g Fourier, wavelet, contourletetc and thereafter a proper thresholding technique is applied to various subbandsto remove the noise and finally inverse transform is applied to bring the signal back into the original domain. In spatial domain, sparsity in the image is exploited for better denoising which is abundantly present in the video as well. A local or temporal search window is used to exploit the sparsity present in the signal. NLM[1] and extended version NLM video [2] denoising technique are among them. Sparsity present in the same image as well as in the neighbouring frames are exploited for better denoising in the latter case. Many spatial domain techniques compute motion between the frames and further compensate it before denoising. In the proposed method we don't compensate the motion prior to denoising which is computationally expensive. NLMV technique itself is computationally expensive as similar patch search has to be carried out in the same image as well as in the neighbouring frames of the video sequence. In the proposed technique we propose to speed-up NLMV technique by carrying out denoising process in lower dimensional subspace. Earlier works on MR image sequences consider Gaussian perturbed MR images and fail to preserve the edges and structural details. However, noise in the MR image is Rician distributed. In the next section we will elaborate the reason for Rician noise assumption. As mentioned earlier removing Rician perturbed noise from MR image sequence is quite difficult task. In our work we have done so by using PCA technique. Quality metrics used for evaluation is Peak Signal to Noise ratio (PSNR), Bhattacharya coefficient (BC), Univeral quality index (UQI) and visual comparisons. Section II & III, discuss about noise characteristics in MR images and NLM theory. The proposed method is discussed in section IV. The optimal parameter selection is also discussed in the same section. Results and discussions are carried out in section V and finally we conclude in section VI.

II. The distribution of Noise in MR images

Nonlocal means filter works very well on additive white Gaussian noise. However fails for Rician noise as Rician noise is signal dependent. The MR acquisition process introduces Rician noise to the MR system. Detecting and preserving edges in Rician corrupted MR image is a challenging task. Rician noise degrades image both qualitatively and quantitatively. Detectability of MR images gets drastically reduced due to bias which is introduced by a Rician noise. Preserving edges and structures for and structures for images corrupted with Rician noise becomes more difficult as Rician noise is signal dependent and hence difficult to remove which can be observed in Table I. It can be observed that MR images perturbed with Rician noise results lower PSNR compared to Gaussian perturbed MR images.Rician distribution has a special featurein regions of high pixel intensity, when noise reduces to a Guassian distribution and in low intensity regions noise distribution tends to Rayleigh distribution.

The complex MR data $X = X(i), \quad i \in \Omega$ is model as,

$$X = X_{Re} + jX_{Im} \quad (1)$$

$$X_{Re} = Scos(\theta) + \xi_1 X_{Im} = Ssin(\theta) + \xi_2 \quad (2)$$

where X_{Re} and X_{Im} are real and imaginary components of the data,which further gets affected by $\xi_1$andξ_2, iid random noise with σ as variance.

$$X_{Re} = Scos(\theta) + \xi_1 \quad (3)$$

$$X_{Im} = Ssin(\theta) + \xi_2 \quad (4)$$

Here $S = S(i),\ i \in \Omega$ is the original MR image and θ is the phase.Magnitude of MR image can be given by,

$$|X| = \sqrt{(Scos(\theta) + \xi_1)^2 + (Ssin(\theta) + \xi_2)^2} \quad (5)$$

Since the computation of magnitude involves a nonlinear function, the distribution of $|X|$ becomes Rician and is represented as,

$$P(X|S,\sigma) = \frac{X}{\sigma^2} e^{\frac{-(X^2+S^2)}{2\sigma^2}} I_0(\frac{XS}{\sigma^2}) \quad (6)$$

Here I_0denotes the modified Bessel function of first kind with order zero, S is the noiseless signal, σ^2 is the noise variance and X is the observed MR magnitude. From the above equation it is clearly observed that for low intensity regions, i.e., when σ^2approaches zero, the expression leads to a Rayleigh PDF i.e.,

$$P(X|S,\sigma) = \frac{X}{\sigma^2} e^{\frac{-X^2}{2\sigma^2}} \quad (7)$$

and wherever the signal intensity is high the above PDF approaches a Gaussian distribution.

$$P(X|S,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(X-\sqrt{S^2+\sigma^2})^2}{2\sigma^2}} \quad (8)$$

According to Nowak [3] we can write,

$$|X|^2 = (Scos(\theta) + \xi_1)^2 + (Ssin(\theta) + \xi_2)^2$$

Taking the expectation on both the sides yields,

$$E[X^2] = E[(Scos(\theta) + \xi_1)^2 + (Ssin(\theta) + \xi_2)^2]$$

$$= E[S^2\cos^2(\theta) + {\xi_1}^2 + 2S\cos(\theta)\xi_1 + S^2\sin^2(\theta) + {\xi_2}^2 + 2S\sin(\theta)\xi_2$$

$$= E[S^2 + 2S(\cos(\theta)\,\xi_1 + \sin(\theta)\,\xi_2) + {\xi_1}^2 + {\xi_2}^2]$$

$$= E[S^2] + 2E[S]E[\xi_1]\cos(\theta) + 2E[S]E[\xi_2]\sin(\theta) + E[{\xi_1}^2] + E[{\xi_2}^2] = \mu_S^2 + 2\sigma^2 \quad (9)$$

Here bias introduced is $2\sigma^2$,where ,$\sigma = \sqrt{\frac{\mu}{2}}$where μ is the mean value. For correlated data, authors in [4] have estimated and filtered noise from correlated multiple coil MR data, and in [5] noise in a single and multiple coil MR data is estimated by statistical models.

III. THE NON LOCAL MEANS THEORY

In local neighborhood filters a small neighborhood local to the pixel to be denoised is considered. It is based on the assumption that pixels which are similar to the center pixel lies spatially close to it. But when we observe any natural image we often find structures or patterns getting repeated i.e., extensive amount of self-similarity appears in the same image. An example of self-similarity is displayed in Fig.1. For illustrative purpose only three pixels p, q_1 and q_2 are shown with their respective neighbourhoods in the figure. The neighbourhoods of pixel p and q_1 are quite similar though they are spatially apart. On the contrary, the neighbourhood of q_2 which is spatially close to p is not similar photometrically, demonstrating the fact that adjacent pixels tend to have similar neighbourhoods but non-adjacent pixels may also have similar neighbourhoods when there are repeated structures in the image. These similar neighborhoods are exploited for the first time in nonlocal means filter for a better estimation of the noisy pixel. Buades et al. proposed nonlocal means filter [1,2].

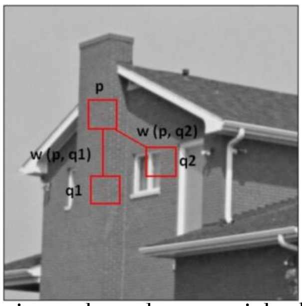

Fig 1: Illustration of nonlocal patch similarity. q_1 has a larger weight than q_2 because of more similarity.

IV. THE PROPOSED METHOD USING PRINCIPAL COMPONENT ANALYSIS

NLMVdenoising technique which is used in the proposed method to denoise MR images corrupted by Rician noise, we get more similar patches compared to single image denoising. However NLM framework is expensive computationally. PCA computation for single image denoising has been expensively studied in various literature. In the proposed method, we compute PCA globally and select very significant eigenvectors that depends on image type and noise level. We carry out extensive experimentation to fix the dimensionality for the proposed method. The dimensionality of the spce is reduced by projecting thus selected few eigen vectors on each and every frames. Further denoising process is carried out in the reduced dimensionality subspace as shown in Fig [2]. A spatial neighborhood around pixel i of frame t shown in orange colored square box is compared for all similar neighborhoods in adjacent frames including the current one shown with green colored square boxes. Similar patches for a given patch are searched in a search window shown with blue colored square boxes for all shown frames.

The stepwise denoising procedure is as given below.

a] Pre-process a given video for shot boundary detection such that a group of frames are quite similar in visual content:

This simple and effective histogram difference method (HD) proposed in [6] for temporal segmentation is given by,

$$\delta(t) = \sum_{i=0}^{255} |his_{(t)}(i) - his_{(t-1)}(i)| \qquad (10)$$

b] Patch collection for a representative frame within a shot.

c] Compute the covariance matrix for the entire set of image patches

d] Let $(q_1, q_2 \ldots q_d)$ be the corresponding set of orthonormal bases of the eigenvectors associated with the few selected eigenvalues $(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d)$ of the covariance matrix. We will restrain ourselves to the subspace by the first d vectors.

e] Sort the order with respect to the magnitude of their corresponding eigen values and select only the top d significant eigenvectors.

f] Computation of the pairwise distance between the current and the neighborhood patch.

g] Finally estimate the noisy pixel i in frame t.

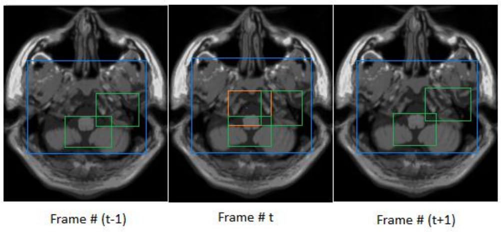

Fig.2: Illustration of spatio-temporal search for similar patches

Table I: Illustration of the effect of Rician and Gaussian noise for a T1-w simulated brain image on PSNR for the same noise level.

Noise variance(%)	Rician noise	Guassian noise
5	29.76	30.64
9	24.60	25.48
13	21.39	22.35
17	19.10	19.97
21	17.28	18.13

A. Bias Correction

Bias correction has to be compulsorily carried out as NLM filter provides good results only for i.i.d random noise. The bias present in the signal $2\sigma^2$ part has to be subtracted from the final result.

$$E[{X_i}^2] = \mu_S^2 + 2\sigma^2 \qquad (11)$$

$\mu_S^2$is the weighted average of square magnitude of original image data. Thus we observe that the measured value ${X_i}^2$ is over estimated by $2\sigma^2$, which is termed as Rician bias.

Considering the special characteristics of the Rician noise, filtering is performed on squared magnitude of the image. Hence the final denoised magnitude MR image is obtained as shown below.

Computation of the new value of$i$ of magnitude image I is as follows,

$$UNLM_L(I(i)) = \sqrt{{\hat{u}_d}^2(i) - 2\sigma^2} \qquad if \;\; NLM_L(I(i))^2 \geq 2\sigma^2 = 0 \qquad \text{otherwise} \;\; (12)$$

B. Selection of Optimal Parameters

The filtering parameter (h) is a dependent parameter on both standard deviation σ of the noise and the dimensionality d. And hence filtering parameter h is computed such that the output PSNR is maximized for each combination of d and σ. Here we have considered both simulated as well as clinical MR image data sets. MR images are simulated with i.i.d random noise with varying σ values. For clinical MR images, noise can be estimated by computing the noise from background of MR images. The thresholding of background is selected by Ostu [3] thresholding technique.Dimensionality(d) of the subspace plays a very important role in computational savings and hence has to be selected carefully. An optimal value of dimensionality d depends on the type of the MR sequence. If MR sequence has more details and structural features with large motion, higher dimensionality value has to be chosen.

V. RESULTS AND DISCUSSION

In this section we present the results for MR image perturbed with NLM using principal component analysis. For better result, we find out optimal filtering parameters for the proposed method. We extensively carry out experiments for varying patch size, window size etc and fix suitable parameters which provides good results. The metrics used for evaluation are PSNR, BC, UQI and visual comparison.

A. Generation of Rician Noise

Procedure to simulate images corrupted with Rician noise is quite different. Firstly, two images have been generated and then Gaussian noise is added in complex domain [7].

$$S_r(x_i) = S(x_i) + \xi 1(x_i), \qquad \xi 1(x_i) \sim \mathcal{N}(0,\sigma) \qquad (13)$$

$$S_i(x_i) = \xi 2(x_i), \qquad \xi 2(x_i) \sim \mathcal{N}(0,\sigma) \qquad (14)$$

where S is MR image with high SNR value, σ is the standard deviation of the Gaussian noise.

Noisy image $S_n(x_i)$ is computed as,

$$S_n(x_i) = \sqrt{S_r(x_i)^2 + S_i(x_i)^2} . \qquad (15)$$

We start our experiments by adding 5%, 9%, 13%, 17% and 21% Rician noise.

B. Effect of Filter Parameters

There are three important parameters which influence the denoising process and hence should be selected carefully.

a) Length of the neighbourhood window.
b) Length of the search window.
c) Filtering parameter (h and h')

To select the best parameters, experiments are carried out by varying neighbourhood side length N_s and search window side length S_s for MR images corrupted with varying level of Rician noise ($5\% - 21\%$). Results have been reported only for one value of low and one value of high noise level i.e., 5% and 13%. For other noise levels, we have observed a similar trend in the output. Fig.3. shows the effect of neighbourhood sidelength N_s on denoised output

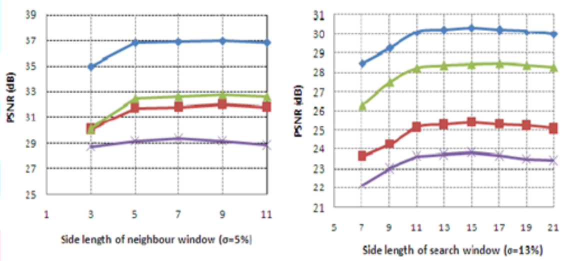

Fig.3: Illustration of effect of filter parameters on denoised result of T1-weighted simulated image (top to bottom): effect of neighbourhood size on denoised result and effect of search window size on denoised result for different noise levels.

C. Performance Comparison

We compare the proposed method with the following known methods.

a) NLM filter. We have selected parameters as suggested in the paper.
b) Unbiased NLM method [8] using 11X11 search window, 5X5 neighbourhood window and filtering parameter h = 1.2 ∗ σ as suggested in the paper.
c) Coup´ e technique [9] using parameters suggested by the author. For fair comparison we have compensated the bias here. We refer this method as unbiased fast nonlocal means (UFNLM).For this part of our experimentation, we have taken clinical data from **mr-tip.com**. Better results are obtained for the proposed method as observed from Fig.4 in terms of BC and UQI. Fig.5shows high SNR clinical images which are further simulated by adding different levels of complex Gaussian noise. We have considered one T1-weighted and two T2-weighted brain images with a resolution of 251X301X181 pixels as high SNR images. Here also we can observe the shift in the output image in case of original NLM method, UFNLM preserves the edges.Table. II provides the comparative results of PSNR for different denoising methods for clinical data set. From this table we observe that superior results are obtained for the proposed method almost everywhere in terms of PSNR, however a slight decrease in PSNR value is observed at 5% noise level. Here we can observe that at lower noise levels both UNLM and UFNLM works better than the proposed method.

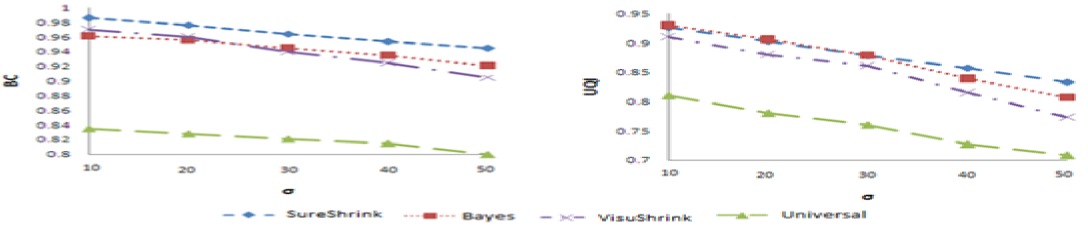

Fig 4. BC and UQI result on T2-weighted clinical image.

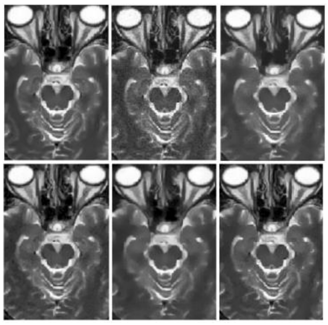

Fig.5: Comparison of denoised result on a T2-w clinical head image. Left to right, top to bottom: input MR image, noisy MR image ($\sigma = 9\%$), results of NLM, FUNLM, UNLM and the proposed method.

Table II: Comparative results of PSNR (dB) for different denoising algorithm on aclinical data set.

	T1-w clinical image			T2-w clinical image1			T2-w clinical image2		
Noise level	5%	13%	21%	5%	13%	21%	5%	13%	21%
NLM	31.63	24.97	21.01	27.89	19.82	15.41	27.63	19.99	15.37
UFNLM	32.30	27.73	24.11	28.98	23.25	19.21	29.74	23.36	19.00
UNLM	32.63	28.07	24.91	29.33	23.23	20.08	30.13	23.73	20.03
Proposed	32.28	28.49	25.13	28.33	23.83	20.29	29.53	24.31	20.19

VI. CONCLUSIONS

In this paper, we worked on Rician perturbed MR images. Unlike the methods where over smoothing is observed due to which edges and fine structures are not lost, the proposed method preserves edges and structural details very well. In addition to these the proposed method higher speed and better accuracy. The proposed method makes use of principal component analysis technique for this dual purpose. The proposed algorithm works very well with a wide variety of MR image sequences that outperforms all other techniques in comparison qualitatively and quantitatively.

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